Segmentation Based Image Scanning

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Abstract. *The submitted paper deals with separate scanning of individual image segments. A new image processing approach based on image segmentation and segment scanning is presented. The resulting individual segments 1-dimensional representation provides higher neighbor pixel similarity than the 1-dimensional representation of the original image. This increased adjacent pixel similarity was achieved even without application of different recursive 2-dimensional scanning methods* [4]*, such as Peano-Hilbert scanning method* [1]*. The resulting 1-dimensional image representation provides a good base for applying lossless compression methods, such as the entropic coding. The paper contains also results analysis of the traditional method scanned segment pixels and adjacent pixel differences from the entropy point of view. As these results indicate the lossy compression methods could be applicable using this approach as well and might improve the final results as confirmed by simple prediction algorithm results presented in this paper. More complex and sophisticated lossy compression algorithms application will be a part of the future work.*

Keywords

Segmentation, scanning, adjacent pixel similarity, pixel differences.

1. Introduction

The majority of image processing methods provide image transformation from the 2-dimenstional representation into the 1-dimenstional by exploiting different image characteristics.

The scanning algorithms focus is on the nearby pixel similarity in the whole image [4] or in the image rectangular parts [3]. They are designed to exploit this characteristic to improve the autocorrelation in the resulting 1-dimensional image representation in means to maximize the adjacent pixel correlation.

Improving the image autocorrelation function can be also achieved by another approach – using image segmentation. The outcome of the segmentation process is a set of image segments, each covering a continuous area of similar pixels from the original image. The segments are then treated and processed as individual units. Since the segments are irregular areas, the scanning is performed using standard raster algorithm.

The resulting sequence of pixels is processed as required by the particular application - like lossless compression. An example for lossless image compression can be taken the popular GIF format, which is based on the Lempel-Ziv sequence compression algorithm [2], or some of the entropic coders (ARJ, RAR …).

The lossy compression methods can be used as well for the final image processing step. Prediction algorithms application on the resulting sequence is the most obvious one considering the final sequence characteristics. The simple lossy compression method presented results provided in this paper indicate the possible improvement. The further work and analysis will be more focused on the application of more complex lossy compression methods.

2. Image Segmentation Method

For the image segmentation procedure already existing segmentation algorithm was chosen – JSEG. The choice was made based on the segmentation criteria (pixel similarity) used by the JSEG [5].

The JSEG algorithm for segment determination transforms the original image into so called J-image, which consists of "peaks" and "valleys". The J-image corresponds to measurements of local image inhomogeneities at different scales. In turn the „valleys" in the image correspond to homogeneous regions and the „peaks" correspond to potential boundary locations [5]. A spatial segmentation algorithm is based on growing regions from the valleys of the J-image to achieve segmentation. J-images correspond to measurements of local image inhomogenities at different scales. For the case when an image consists of several homogeneous color regions, the color classes are more separated from each other and the value of J is large. On the other hand, if all color classes are uniformly distributed over the entire image, the value of J value tends to be small.

At the beginning, a set of small initial areas are determined to be the bases for region growing. These areas have the lowest local J values and are called valleys. In general, finding the best set of valleys in a region is a nontrivial problem and the used algorithm is described in [5].

After region growing, an initial segmentation of the image is obtained. It often has over-segmented regions. These regions are then merged based on their color similarity. Distances between two neighboring regions are calculated and stored in a distance table. The pair of regions with the minimum distance is merged together. And the process is repeated but the new merged area characteritcs is recalculated and the new values are taken in the region distance computation process [5].

Each segmentation algorithm has a „map" as an outcome of the whole process. The map is an image that has the same dimensions as the original one. Each segment is represented with different grayscale color level in the map, i.e. pixels of the same grayscale level belong to the same segment. Because the segments differ from image to image, the map is created for each image separately. Results show that JSEG provides a good segmentation on a variety of gray-level as well as color images [5].

3. Scanning Method

As mentioned our presented approach treats each segment separately as a unit. Thus each segment is scanned individually. Due to the irregular character of the segments 2-dimensional recursive scanning algorithm application would be too complex. For simplification two basic scanning methods were used to determine the approach efficiency. The 1st is the standard raster method and the 2nd method is the non-recursive 2-dimensional continual scanning algorithm as mentioned in [3]. Because the segments tend to have irregular shape unlike whole images, both scanning algorithms had to be modified to handle and scan also nonrectangular areas. The modification is depicted in Fig. 1 and Fig. 2.

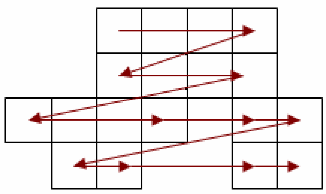


Fig. 1. Raster scanning algorithm - modification for non-rectangular areas.

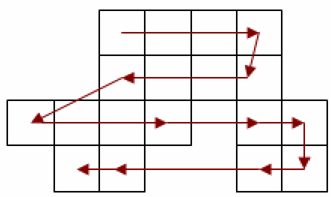


Fig. 2. Continuous scanning algorithm - modification for non-rectangular areas.

3.1 Scanning Image Pixel Processing

To gain more considerable results for the proposed image processing approach efficiency determination, both scanning procedures have 2 modes of operation in addition to the description above when processing the image pixels.

In the scanning method described above the specified sequence in which the pixels are scanned is referred to as the "scanning path". The first mode simply scans the pixels as they are without altering them. This results in 1-dimensional representation of the scanned image segment.

The second mode focuses on the neighbor pixels similarity. In this case the neighbor pixels are successive pixels along the scanning path. When the segment is being processed, the neighbor pixels from the scanning path don't have to be necessary adjacent pixels in the original image. To analyze better the adjacent pixel similarity along the scanning path the difference between adjacent pixels is taken and stored in the resulting 1-dimensional representation instead of the pixel value.

The first reference pixel of the image or segment is stored without any modification. The stored values for other pixels are computed according to the following relation

$$d_i = x_i - x_{i-1} \tag{1}$$

where x_i and x_{i-1} are the successive pixels along the scanning path.

4. Entropy

For the result analysis we used an objective criterion – entropy. It depicts what theoretical minimal limit of bitrate is achievable to encode the original message without any information loss. In other words, it defines the limit for shrinking the original message (image) without losing any informational value. It is based on the probability of the message symbols. The basic entropy calculation formula is

$$L = -\sum_k p_k \cdot \log_2(p_k) \tag{2}$$

where p_k is the probability of the k-th symbol within the input data.

Many encoders use the entropy theory for their coding technique, e. g. Huffman and Arithmetic coder.

For the result comparison between the original image scanning and the segment scanning the final entropy for all image segments is evaluated (3):

$$E_s = \sum_i \frac{E_i \cdot s_i}{n_1 \cdot n_2} \tag{3}$$

where E_s is the final entropy for all image segments, E_i is the entropy for the i-th image segment, s_i is the number of pixels in that segment, n_1 and n_2 are the original image dimensions.

5. Lossy Compression Method

Based on the resulting image pixel sequence characteristics the lossy compression methods application should also improve. For evaluating the lossy compression application a DPCM prediction method was applied. For simplicity the prediction method used the 1bit for the residual representation. The residual quantization was adapted to each image individually based on the average difference between the adjacent pixels in the resulting 1-dimensional representation.

$$E = \frac{1}{P-1}\sum_{n=1}^{p-1}\left|x(n+1)-x(n)\right| \tag{4}$$

where P is the image pixel count, $x(n)$ is the n-the pixel in the resulting 1-dimensional representation.

The purpose of this simple prediction method application is to initially determine if the outcome of the whole image process improves or not.

6. Results

The image processing approach results were compared using entropy as the objective criterion to see how the algorithm performs.

The following tables show the results when the standard method was used for image and segment scanning in both modes:

- mode 1 – original pixel value,
- mode 2 – difference between adjacent pixels along the scanning path.

In each case the first table shows the individual segments entropy and in the second table the final segments entropy (3) is compared to the original image entropy. In addition to determine the overall processing efficiency the bits per pixel rate of the encoded map is provided and considered in the final results as well. Because the map is crucial for the correct image retrieval process it must be added to the processed image data. Here the best (underscored) and worst (italic) results are highlighted.

The encoded map for the image Boris with 7 segments requires 0,06 bits per pixel. This amount of additional information must be added to the final entropy of the segmented Boris image. Even than the result is still at 0,86 bit per pixel better than of the original image.

For the Cindy image the map is encoded at the rate of 0,07 bits per pixel. Also in this case when adding this amount to the final segmented image entropy the result is still at 1,14 better.

Fig. 3. Image Boris with 256x256 pixels, 8 segments.

Segment	Raster scanning		Continual scanning	
	Entropy - mode 1	Entropy - mode 2	Entropy - mode 1	Entropy - mode 2
1	3,35	4,29	3,35	4,23
2	5,99	5,91	5,99	5,86
3	1,34	2,00	1,34	1,94
4	4,47	5,40	4,47	5,37
5	3,17	4,18	3,17	4,14
6	3,04	4,46	3,04	4,41
7	3,02	4,20	3,02	4,06

Tab. 1. Entropy values for individual Boris image segments when using both scanning methods in both modes.

	Original	Image Differences	Raster mode 1	Raster mode 2	Continual mode 1	Continual mode 2
Entropy	*6,04*	5,66	<u>5,12</u>	5,54	<u>5,12</u>	5,5

Tab. 2. Image Boris 256x256 pixels – final entropies.

Segment	Raster scanning		Continual scanning	
	Entropy - mode 1	Entropy - mode 2	Entropy - mode 1	Entropy - mode 2
1	5,77	5,61	5,77	5,58
2	3,17	4,64	3,17	4,53
3	3,15	3,79	3,15	3,76
4	5,35	5,70	5,35	5,65
5	4,61	5,52	4,61	5,50
6	4,20	5,87	4,20	5,81
7	4,30	5,15	4,30	5,07
8	3,87	4,24	3,87	4,05
9	3,58	4,62	3,58	4,48
10	3,49	4,62	3,49	4,41

Tab. 3. Entropy values for individual Cindy image segments when using both scanning methods in both modes.

	Original	Image Differences	Raster mode 1	Raster mode 2	Continual mode 1	Continual mode 2
Entropy	*6,04*	5,5	<u>4,83</u>	5,32	<u>4,83</u>	5,26

Tab. 4. Image Cindy 256x256 pixels – final entropies.

Fig. 4. Image Cindy with 256x256 pixels, 10 segments.

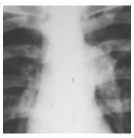
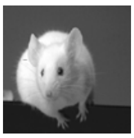
As seen from the tables, in the presented cases the proposed algorithm results in the decrease of the final bits per pixel ratio. The improvement to the original image remains even when taking into account the map from the segmentation process, but of course the improvement is lower. Tab. 5 contains entropy results comparison from other various images.

	Original	Image Diffe-rences	Raster mode 1	Raster mode 2	Conti-nual mode 1	Conti-nual mode 2
girl	*5,57*	4,64	4,69	4,62	4,69	4,57
reagan	*7,06*	5,56	6,42	5,58	6,42	5,53
wet	*5,56*	5,3	4,52	5,24	4,52	5,19
xray	*7,29*	4,21	6,56	3,76	6,56	3,74
mouse	*5,1*	3,07	3,37	2,99	3,37	2,93
bike	*7,3*	5,26	6,58	5,02	6,58	4,99

Tab. 5. Final entropy results for images of 256x256 pixels.


a.)

b.)

c.)

d.)

e.)

f.)

Fig. 5. Images a.) girl, b.) Reagan, c.) wet, d.) xray, e.) mouse, f.) bike.

The tables also show that in most cases the differences between adjacent pixels in the segments along the scanning path tend to have lower entropy as the original pixels value in those segments. For the cases that have the opposite characteristics, closer look at the scanned segments and their histograms gives the answer why it is like this. Below the comparison of 2 segments from the image Cindy and their histograms for the raster scanning method using both modes is given.

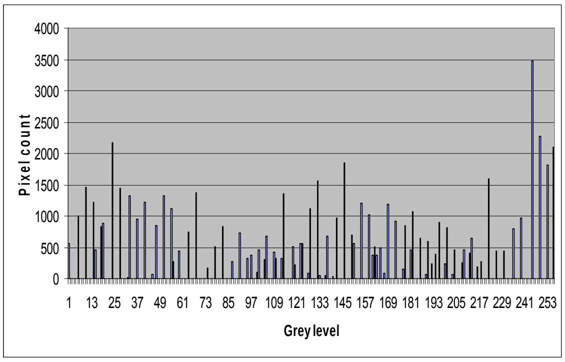


Fig. 6. Original image histogram.

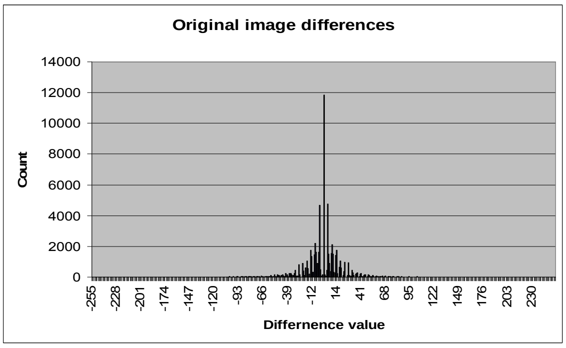


Fig. 7. Histogram of image differences.

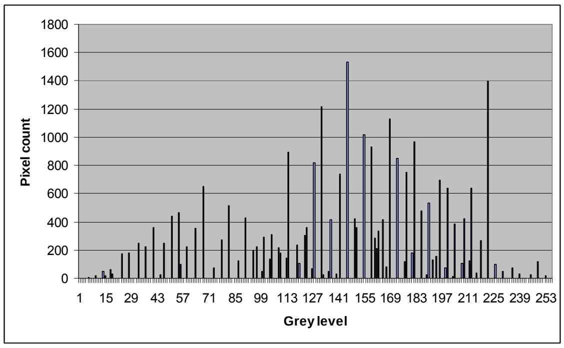


Fig. 8. Histogram of the raster scanned segment1 from the image Cindy using mode 1.

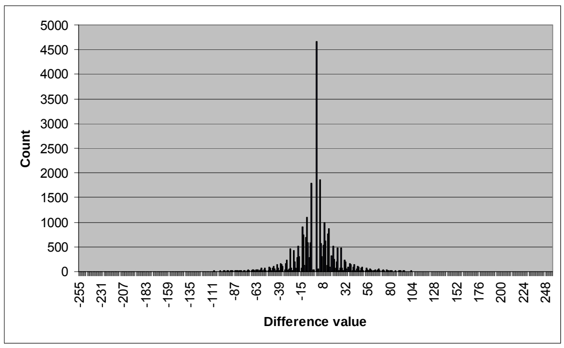


Fig. 9. Histogram of the raster scanned segment1 from the image Cindy using mode 2.

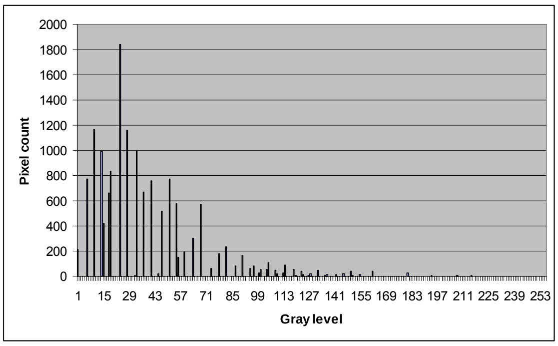


Fig. 10. Histogram of the raster scanned segment5 from the image Cindy using mode 1.

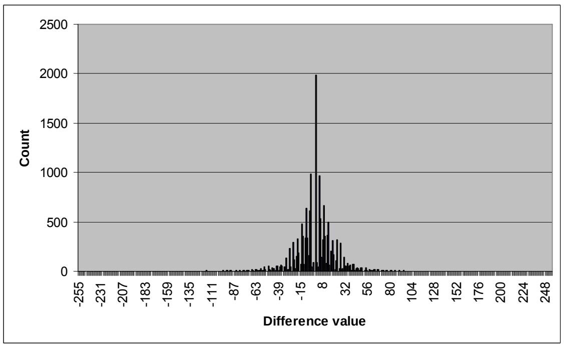


Fig. 11. Histogram of the raster scanned segment5 from the image Cindy using mode 2.

Based on the provided histograms examination it can be seen the scanned segments contain pixels of gray levels from a small set, i.e. each segment contains only few levels of gray. Because of this feature the segment entropy is lower than the entropy of the original image.

On the other hand the mode 2 scanned segments, e.g. the adjacent pixel difference is stored, as mentioned in most cases tend to have lower entropy than segments scanned with mode 1. For the cases that don't have this characteristic, the reason can be determined from the submitted histograms. The mode 2 scanned segments contain values from wider range than pixels from the segment. The wider value range is due to the differences, which can vary in the range twice the size as the gray levels of the pixels. So from the entropy point of view, e.g. for lossless coding, the difference scanning gains lower improvement than the pixels scanning.

The introduced method improves the final result for lossless method application on such processed images.

The gained entropy results from the pixel differences scanning indicate the direction of the future study and work – lossy compression methods. The submitted histograms of the differences scanning approve it as well, because the majority of difference values in given segments are concentrated near the value 0 and only few difference values are further away Fig.9 and Fig. 11.

For the prediction application results analysis the objective criterions MSE and the PSNR values were used. The best results (underscored) and worst (italic) results are highlighted.

DPCM	Original		Segmented	
	MSE	PSNR	MSE	PSNR
girl	*1123*	*17,63*	574,9	20,53
reagan	*299,4*	*23,36*	172,5	25,76
wet	*590,4*	*20,42*	491	21,22
xray	*265,9*	*23,88*	258,2	24,01
mouse	*627,8*	*20,15*	99,6	28,147
bike	*1000*	*18,13*	741,7	19,428
cindy	*557,8*	*20,67*	441,3	21,68
boris	*390,9*	*22,21*	197,3	25,19

Tab. 6. MSE and PSNR values for the DPCM lossy compression method application.

As the results in the table indicate the results were improved and for some pictures even such a simple prediction method led to a good improvement.

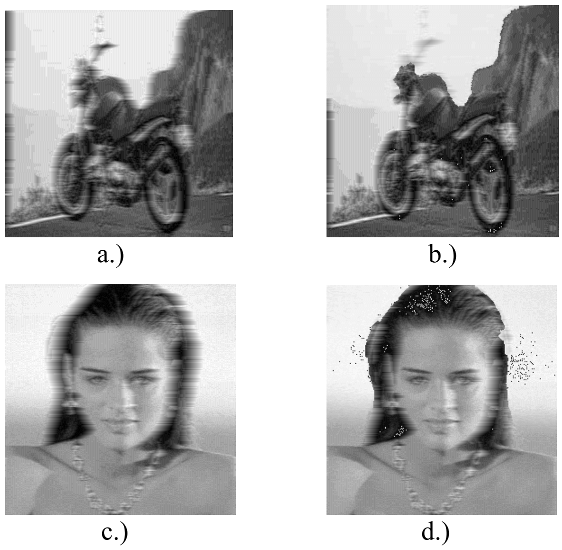


Fig. 12. DPCM application resulting images a.) bike scanned using standard scanning method, b.) bike scanned using segmentation based scanning method, c.) girl scanned using standard scanning method, d.) girl scanned using segmentation based scanning method.

As seen from the images the segmentation scanned images preserve better the edges, especially those which are also the segment boundaries.

7. Conclusion

The described image processing approach uses image segmentation. The individual segments are scanned separately using standard raster scanning method and 2-dimensional non-recursive continual method. In addition not only pixels are scanned along the scanned path but also differences between them. This approach increases the neighbor pixel similarity in the resulting 1-dimensional image representation and thus decreases the final image entropy.

The pixel scanning method is suitable for lossless coding applications, which can exploit the increased autocorrelation function of the result representation.

The information gained in this paper, especially the differences value distribution shown in the histograms, can be a good initial point for further work and research, specifically in the lossy compression techniques application. The difference values distribution could be useful also in the improvement of error concealment methods [6], because the quality of repaired image blocks strongly depends on characteristics of surrounding image regions.

The final 1-dimensional image representation after segmentation based scanning provides good characteristics which can be exploited by the prediction coding techniques.

For the future work implementing more complex scanning algorithms using space filling curves could improve even more the neighbor pixel similarity and entropy results. In the lossy compression applications the future work will focus on designing more complex and sophisticated algorithm which improve the final results.

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